AMENDMENTS TO THE CLAIMS

1. (Currently amended) A method comprising ~~at least one of~~ training ~~and using~~ a neural network to reduce artifacts in spatial domain representations of images that were compressed by a transform method and then decompressed, the training including:

accessing a training set that includes first and second images, the second image being a version of the first image that was compressed by a transform method and then decompressed;

using the neural network to generate an output image from the second image of the training set;

determining differences between the output image and the first image, including generating error neighborhoods; and

using the error neighborhoods to adjust connection weights of the neural network.

2. (Currently amended) The method of claim 9, wherein scaled coding is used~~1, wherein the neural network is trained to reduce the artifacts using a training set, the training set including first and second images, the second image being a version of the first image that was compressed by a transform method and then decompressed~~.

3. (Cancelled)

4. (Currently amended) The method of claim [[3]] 1, wherein the transform method included dividing the first image into pixel blocks; and wherein pixel locations within their transform blocks are also supplied to the neural network during the training.

5. (Currently amended) The method of claim 1, ~~3, wherein determining the differences includes generating error neighborhoods;~~ wherein

the error neighborhoods are used to generate derivatives of total error with respect to a neighborhood of errors; wherein gradients are computed from the derivatives; and wherein the gradients are used to adjust the connection weights.

6. (Currently amended) The method of claim 5, further comprising punishing spatially correlated errors in the error neighborhoods.

7. (Currently amended) The method of claim [[5]] 1, wherein the error neighborhoods are used by a non-gradient descent algorithm ~~is used~~ to adjust the connection weights.

8. (Currently amended) The method of claim [[3]] 1, wherein the neural network processes more than one pixel at a time.

9. (Currently amended) The method of claim [[3]] 1, wherein input and output data of the neural network are coded to improve the neural network accuracy.

10. (Currently amended) The method of claim 9, wherein relative coding is used.~~1, wherein the neural network is used by inputting at least a luminance channel of the spatial domain representation to the neural network~~.

11. (Original) Apparatus comprising a processor programmed with the trained neural network of claim 1.

12. (Original) An article comprising computer memory encoded with the trained neural network of claim 1.

13. (Cancelled).

14. (Cancelled).

15. (Currently amended) Apparatus comprising computer memory encoded with a neural network; and means for training the neural network to reduce artifacts in spatial domain representations of images that were transformed from a spatial domain representation to a frequency domain and back to the spatial domain representation, the training means accessing a training set that includes first and second images, the second image being a version of the first image that was compressed by a transform method and then decompressed; using the neural network to generate an output image from the second image of the training set; determining error neighborhoods between the output image and the first image; and using the error neighborhoods to adjust connection weights of the neural network.

16. (Currently amended) The apparatus of claim 15, further comprising performing one of relative and scaled coding on input and output data of the neural network to improve neural network accuracy ~~wherein the neural network includes a plurality of connection weights; and wherein the training means uses a first image to generate an output image; determines differences between the output image and a second image; and uses the differences to adjust the connection weights of the neural network, the first image being a version of the second image after compression in the frequency domain and then decompression~~.

17. (Currently amended) The apparatus of claim [[16]] 15, wherein the transform method included dividing the first image into pixel blocks; and wherein the training means also uses pixel offsets with respect to the transform blocks to generate the output image.

18. (Currently amended) The apparatus of claim [[16]] 15, ~~wherein determining the differences includes generating error neighborhoods;~~ wherein the error neighborhoods are used to generate derivatives of total error with

respect to a neighborhood of errors; wherein gradients are computed from the derivatives; and wherein the gradients are used to adjust the connection weights.

19. (Original) The apparatus of claim 18, wherein the training means also punishes spatially correlated errors in the error neighborhoods.

20. (Currently amended) The apparatus of claim [[18]] 15, wherein the error neighborhoods are used by a non-gradient descent algorithm ~~is used~~ to adjust the connection weights.

21. (Currently amended) The apparatus of claim [[16]] 15, wherein the training means generates input vectors for the pixels in the first image, and processes the input vectors independently of one another to generate the output image, each input vector including a neighborhood of pixels.

22. (Cancelled).

23. (Currently amended) An article for a processor, the article comprising computer memory encoded with a program for instructing the processor to train a neural network to reduce artifacts in images that were compressed in the frequency domain and then decompressed, the training including accessing first and second images, the second image being a version of the first image that was compressed by a transform method and then decompressed; using the neural network to generate an output image from the second image of the training set; determining error neighborhoods between the output image and the first image; and using the error neighborhoods to adjust connection weights of the neural network.

24. The article of claim 23, further comprising performing one of relative and scaled coding on input and output data of the neural network to improve neural network accuracy~~wherein the neural network includes a plurality of~~

~~connection weights; and wherein the training includes using a first training image to generate an output image, determining the differences between the output image and a second training image, and using the differences to adjust the connection weights, the first training image being a version of the second image after compression in the frequency domain and then decompression~~.

25. (Currently amended) The article of claim [[24]] 23, wherein the compression of the first image included dividing the first image into pixel blocks; and wherein pixel offsets with respect to the transform blocks are used by the neural network in addition to the first image.

26. (Currently amended) The article of claim [[24]] 23, ~~wherein determining the differences includes generating error neighborhoods;~~ wherein the error neighborhoods are used to generate derivatives of total error with respect to a neighborhood of errors; wherein gradients are computed from the derivatives; and wherein the gradients are used to adjust the connection weights.

27. (Original) The article of claim 26, wherein spatially correlated errors in the error neighborhoods are punished.

28. (Currently amended) The article of claim [[26]] 23, wherein the error neighborhoods are used by a non-gradient descent algorithm ~~is used~~ to adjust the connection weights.

29. (Original) The article of claim 23, wherein input vectors are generated for the pixels in the first image, and wherein the neural network processes the input vectors independently of one another to generate the output image, each input vector including a neighborhood of pixels.